Price Discovery in U.S. Corn Cash and Futures Markets: The Role of Cash Market Selection

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Abstract

Using daily data from 182 spatially separated U.S. cash markets for the years 2006-2011, I investigate price discovery for corn. With a large number of cash markets available, I take into account explicitly the issue of market selection, which has been neglected in previous work. I find that empirical results concerning price discovery based on corn cash and futures markets vary with selection of cash markets. The cointegration relationship between corn cash and futures prices only holds for 52 cash markets based on logarithmic prices. And the informational source roles of futures and cash prices are equal in the long run for 49 out of these 52 markets. In the short run, the unidirectional causality from cash to futures prices is most possible no matter whether the cash market is cointegrated with the futures market or not. While the vast majority of causal relationships are linear, the causality from futures to cash prices is more likely to be nonlinear, especially for cash markets cointegrated with the futures market. For quantitative measures of the relative contributions of the futures market and an associated cointegrated cash market to the price discovery process, information share model and common factor model draw the same conclusion qualitatively and find that the contribution of the futures market is more likely to be small than a cash market.

Keywords: Corn, Error Correction Model, Cointegration, Causality, Price Discovery

JEL Codes: D84, G13, G14, Q13, Q14, R12

1 Introduction

Price discovery, from the perspective of financial markets, is interpreted as an equilibrium price searching process (Schreiber & Schwartz, 1986), a news collecting and interpreting process (Baillie, Booth, Tse & Zabotina, 2002), and an implicit trading implied information incorporation process (Lehmann, 2002). From the perspective of futures markets, price discovery usually refers to the use of futures prices in determining expectations of future cash market prices (Schroeder & Goodwin, 1991; Yang, Bessler & Leatham, 2001; Yang,

Yang & Zhou, 2012), and thus incorporates the aforementioned process-based definition. Farmers, agricultural commodity trading and processing corporations, hedgers, speculators, economists, and policymakers are all concerned about the price discovery performance of commodity futures markets, which provides information to economic entities when they make decisions on production, storage, processing, and consumption (Black, 1976; Yang & Leatham, 1999). The use of commodity futures markets is thus closely related to their price discovery performance (Yang, Bessler & Leatham, 2001; Yang, Yang & Zhou, 2012).

Several statistical tests and methods have been associated with price discovery research. A prediction hypothesis tested in several studies (Yang, Bessler & Leatham, 2001; Yang, Yang & Zhou, 2012) investigates the long-run informational causality between cash and futures markets, an important factor determining the significance of futures markets in price discovery (Purcell & Hudson, 1985). The test imposes restrictions on the loading matrix (equivalently, the matrix of adjustment coefficients) of an error correction model (ECM), such as α defined in case (c) of Equation (1) in Section 2.2, and examines whether a specific price series is weakly exogenous, i.e., whether a zero-row in the loading matrix corresponds to that series. A weakly exogenous series serves as a major information source in the long run and a unidirectional cause of movements in other series. Besides, the Hasbrouck's (1995) information share and the Gonzalo and Granger's (1995) common factor weight measurements can be adopted to quantitatively evaluate the relative contributions of the cointegrated cash and futures prices to the price discovery process. Recent applications of at least one of these two approach to price discovery research in financial markets include Cabrera, Wang and Yang (2009), Chen and Gau (2009), Poskitt (2009), and Tao and Song (2010). The information share model measures the contribution of a specific market by decomposing the innovation of the implicit common efficient price into the innovation of the price of that market while the common factor model assumes the efficient price to be a linear combination of the cointegrated price variables and uses the normalized absolute weight of each variable to calculate its contribution. Futhermore, the linear Granger causality test is popularly employed to explore the short-run informational causality between cash and futures markets, and the nonlinear Granger causality test needs to be applied to handle potential nonlinear relations among variables. Combinational applications of these two tests to price discovery research are common (Bekiros & Diks, 2008a; Qiao, Li & Wong, 2008; Shu & Zhang, 2012; Silvapulle & Moosa, 1999). The linear Granger causality test assumes a parametric linear time series model and determines whether the lags of one variable should be included in the equation for another variable. While the linear Granger causality test has an appealing parametric form, the nonlinear Granger causality test has the advantage that no specific linear parametric form is assumed.

For the U.S. corn market, Garbade and Silber (1983) found that the futures market dominates the cash market in terms of price discovery; Yang, Bessler and Leatham (2001) demonstrated that the futures market leads the cash market in the long run, but futures prices fail to be an unbiased estimate of cash prices; Hernandez and Torero (2010) supported the price discovery role of the futures market. However, empirical evidence can be mixed on statistical test results associated with price discovery research across markets, commodities, and time periods. Particularly, the effect of market selection on results of price discovery research has been discussed, but at least for the U.S. corn market, not addressed explicitly in previous literature. For example, Garbade and Silber (1983) provided cross-commodity evidence of the importance of market size to the price discovery role of a futures market. Schroeder and Goodwin (1990) collected price data for both non-centralized direct and centralized terminal fed cattle markets[1] to explore differences in the regional price discovery process of cash markets between these two market types, and concluded that large volume markets in major cattle feeding regions serve as dominant price discovery locations. Goodwin and Schroeder (1991) tested cointegration relationships of regional cash markets using price data for both direct and terminal slaughter cattle markets, and demonstrated that market volumes and types can influence cointegration significantly. Schwarz and Szakmary (1994) pointed out that price leadership in cash and futures markets is a function of their relative market sizes. Schroeder (1997) indicated that plant level prices, instead of Agricultural Marketing Service ones, are the most relevant price data for market performance analysis. Lyons (2001) explained that a significant share of price determination is not likely to happen in the foreign exchange futures market since it is much smaller than its associated cash market. Cabrera, Wang and Yang (2009) drew a similar conclusion on Euro and Japanese Yen exchange rates. Theissen (2002) revealed that the price discovery contribution of a stock trading system is positively related to its market share. Mattos and Garcia (2004) found that, for Brazilian thinly traded agricultural futures markets, higher trading volume is linked to the existence of long-run equilibrium relationships between cash and futures markets. Bohl, Salm and Schuppli (2011) described the relationship between the investor structure of a stock index futures market and its price discovery function.

This study investigates price discovery between U.S. corn cash and futures markets with a focus on how the results of the aforementioned statistical tests associated with price discovery research change with different cash markets selected for analysis. Correspondingly, the focus of price discovery is broadly defined based on the statistical approaches adopted. The predication hypothesis emphasizes that price discovery happens in a market whose prices do not respond to disturbances in the long-run equilibrium relationship characterized in an ECM, such as $\beta' X_{t-1}$ in case (c) of Equation (1) in Section 2.2. The information share and common factor models quantitatively measure the contribution of a market to the price discovery process by stressing how much that market contributes to the common efficient price through variance and weight decompositions, respectively. The (non)linear Granger causality test exams price discovery via lead-lag relationships among price series and determines whether adding lagged values of a price variable X_{P_1} improves the prediction

[1] The prices of terminal markets are determined at by auction while those of direct markets are decided by negotiated sales in each geographic area (Koontz, Garcia & Hudson, 1990). A terminal market usually has a larger trading volume than a direct market.

power of another price variable X_{P_2} from only X_{P_2} lagged values. Specifically, we attempt to discern whether the long-standing empirical results of cointegration between U.S. corn cash and futures prices and price discovery in the futures market are robust to the selection of cash markets. If so, we show how the futures market leadership changes with selection of cash markets. If not, we show how the relationship between cash and futures markets varies with selection of cash markets.

The remainder of the paper is organized as follows. Section 2 presents the empirical framework. Section 3 describes the data. Section 4 shows the empirical results and Section 5 provides conclusions.

2 Empirical Framework

Since data stationarity affects the modeling of price variables, we first determine the integration order of each price series using unit root tests. Second, we apply Johansen's trace and maximum eigenvalue tests (Johansen, 1988; Johansen, 1991) to investigate cointegration relationships for each pair of cash-futures price series because causality test should be based on an ECM instead of an unrestricted vector autoregressive model (VAR) for cointegrated series as suggested by Engle and Granger (1987). Besides, possible structural breaks in the long-run relationship are explored for each cash-futures price series pair with Hansen and Johansen's (1999) recursive cointegration method which can reveal the (in)stability of the identified cointegration relationship. For each cash market that is (not) cointegrated with the futures market, (a VAR in differences[2]) an ECM is adopted for modeling. With the proper model specification, we perform statistical tests associated with price discovery research discussed in Section 1. For all cash-futures price series pairs, cointegrated or not, a linear Granger causality test based on the raw natural logarithm data is performed. Meanwhile, with the linear relationship between each pair of cash and futures prices being purged away using a VAR in differences or an ECM, the nonlinear Granger causality is tested by applying Diks and Panchenko's (2006) method to the VAR-in-differences- or ECM-filtered residuals. Before the nonlinear Granger causality test, the BDS test (Broock, Scheinkman, Dechert & LeBaron, 1996) is applied to investigate nonlinearities of the residuals and thus determine the appropriateness of the nonlinear test. For each cointegrated cash-futures pair, the prediction hypothesis is tested to examine the long-run informational causality and the information share and common factor models are utilized to calculate the relative contributions of cash and futures markets to the price discovery process.

[2] As discussed in Section 3, the unit root test results show that all of the price series are not stationary in levels but stationary in differences at the 5% significance level.

2.1 Unit Root Test

Two approaches with the null hypothesis of a unit root are adopted to test nonstationarity: the augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) and the Phillips-Perron (PP) test (Phillips & Perron, 1988). Since failure to reject the null of a unit root does not decisively mean that a unit root exists, unit root tests may not behave well in telling a unit root and weakly-stationary alternatives apart. Hence, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski, Phillips, Schmidt & Shin, 1992) with the null hypothesis of stationarity is also applied. These three tests are implemented for both price levels and their first differences. A brief introduction of technical details is given in Appendix A following Zivot and Wang (2006).

2.2 Cointegration and an Error Correction Model

Let a $p \times 1$ vector X_t[3] be represented in an ECM:

$$H_0\colon\ \Delta X_t = \mu + \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t, \text{ where } t = 1, ..., T. \tag{1}$$

In Equation (1), $\Delta X_t = X_t - X_{t-1}$, Π and Γ_i are $p \times p$ coefficient matrices, μ is a $p \times 1$ deterministic term. Three possible cases for Equation (1) of interest are: (a) if Π has full rank p, X_t is stationary in levels and a VAR in levels should be adopted, i.e., $X_t = \mu + \sum_{i=1}^{k} \Pi_i X_{t-i} + e_t$, where $\Pi_1 = \Gamma_1 + \Pi + I_p$, $\Pi_i = \Gamma_i - \Gamma_{i-1}$ for $i = 2, ..., k-1$, and $\Pi_k = -\Gamma_{k-1}$; (b) if Π has zero rank ($\Pi = \mathbf{0}$), it does not contain long-term information and a VAR in differences should be adopted, i.e., $\Delta X_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t$, for X_t being $I(1)$ and not cointegrated; (c) if Π has rank $r \in [1, p-1]$ for X_t being $I(1)$, i.e., X_t has r linearly independent cointegrating vector(s) and $p-r$ common stochastic trend(s), it can be written as $\Pi = \alpha\beta'$, where α and β are $p \times r$ matrices with rank r, and $\beta' X_t \sim I(0)$ is stationary. Π is the long-run impact matrix, and Γ_i for $i = 2, ..., k-1$ are the short-run impact matrices. The rows of β' constitute a basis for the r cointegrating vectors and the elements of α apportion the effect of the cointegrating vectors to the evolution of ΔX_t. Equation (1) thus can be written as $\Delta X_t = \mu + \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t$. Since for any $r \times r$ nonsingular matrix M, we have $\alpha\beta' = (\alpha M)(M^{-1}\beta') = (\alpha M)[\beta(M^{-1})']' = \alpha^{\Delta}\beta^{\Delta}$, the factorization $\Pi = \alpha\beta'$ is not unique and only identifies the space spanned by the cointegrating relations. Further restrictions on the model are needed to establish the uniqueness of α and β.

We adopt the trace and maximum eigenvalue tests (Johansen, 1988; Johansen, 1991) to assess cointegration. Two models are considered in this study: (a) $H_1(r)$: $\mu = \mu_0$ (unrestricted constant), $\Delta X_t = \mu_0 + \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t$, and the cointegrating relations $\beta' X_t$ may have a non-zero mean; (b)

[3] In this study, $p = 2$, and $X_t = \begin{pmatrix} C_t \\ F_t \end{pmatrix}$, where C_t and F_t stand for cash and futures prices, respectively.

$H_1^*(r)$: $\mu = \mu_0 = \alpha\delta^{'}$ (restricted constant), $\Delta X_t = \alpha(\beta' X_{t-1} + \delta^{'}) + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t$, and the cointegrating relations $\beta' X_t$ have a non-zero mean $\delta^{'}$. Both the trace test and maximum eigenvalue tests are based on the estimated eigenvalues, $\hat{\lambda}_1 > \hat{\lambda}_2 > \cdots > \hat{\lambda}_p$, of the matrix Π, whose rank equals the number of non-zero eigenvalues. The eigenvalues equal the squared canonical correlations between ΔX_t and X_{t-1} corrected for lagged ΔX_t and μ, and are thus within the range of zero and one. Furthermore, the recursive cointegration approach by Hansen and Johansen (1999) is employed to test the stability of the cointegration relationship (or lack thereof). Studies such as Bessler, Yang and Wongcharupan (2003), Diamandis, Georgoutsos and Kouretas (2000), Yang (2003), and Yang, Yang and Zhou (2012) have adopted this method for similar purposes. A brief introduction of technical details of cointegration analysis following Zivot and Wang (2006) and the recursive cointegration approach following Hansen and Johansen (1999) is given in Appendix B.

2.2.1 Prediction Hypothesis Test

To determine the long-run informational causality between cash and futures markets, the prediction hypothesis as indicated by Yang, Bessler and Leatham (2001), Yang, Yang and Zhou (2012), and Zhong, Darrat and Otero (2004) is represented as:

$$H_2|H_1\colon\ B^{'}\alpha = 0. \tag{2}$$

For the $p = 2$ case, that is: (1) $\alpha_1 = 0$ if the cash price leads the futures price ($B^{'} = (1\ 0)$), (2) $\alpha_2 = 0$ if the futures price leads the cash price ($B^{'} = (0\ 1)$), and (3) $\alpha_1 \neq 0$ and $\alpha_2 \neq 0$ if a bidirectional information flow exists between the cash price and the futures price ($B^{'} = (1\ 1)$), in the long run, since a weakly exogenous series serves as a major information source and a unidirectional cause of movements in other series. The predication hypothesis thus emphasizes that price discovery happens in a market whose prices do not respond to disturbances in the long-run equilibrium relationship characterized in an ECM, such as $\beta' X_{t-1}$ in case (c) of Equation (1)[4]. Following Yang, Bessler and Leatham (2001), Yang, Yang and Zhou (2012), and Zapata and Rambaldi (1997), the prediction hypothesis is tested jointly with restrictions imposed on the matrix of cointegrating vectors of an ECM, such as β defined in case (c) of Equation (1), if they are not rejected. Particularly, we consider[5]:

[4] To be more specific, $\alpha_1 = 0$ ($\alpha_2 = 0$) indicates that the cash (futures) price does not respond to disturbances in the long-run equilibrium relationship, and $|\alpha_1| = |\alpha_2| \neq 0$ says that the responses of the cash and futures prices to disturbances are of the same magnitude. Based on the ECM in Equation (1), we examine whether the influence of disturbances in the long-run equilibrium relationship, $\beta_1 C_{t-1} + \beta_2 F_{t-1}$, on ΔC_t (ΔF_t) is zero for $\alpha_1 = 0$ ($\alpha_2 = 0$), and whether the influences on ΔC_t and ΔF_t are equivalent in magnitude for $|\alpha_1| = |\alpha_2| \neq 0$.

[5] To be more specific, this hypothesis can be written as:

$$H_{2,\ joint}\colon\ (1\ 1)\begin{pmatrix}\beta_1\\ \beta_2\end{pmatrix} = 0 \Leftrightarrow \beta_1 = -\beta_2.$$

$$H_{2,\ joint}\colon\ R^{'}\beta = 0, \text{ where } R^{'} = (1\ 1) \text{ for the } p = 2 \text{ case.} \tag{3}$$

2.2.2 Relative Contributions to Price Discovery

For a commodity, such as corn, traded in many markets, its price in a specific market is determined by the news collecting and interpreting process in one or more of these markets (Baillie, Booth, Tse & Zabotina, 2002). Two approaches can be adopted to examine the relative contributions of cointegrated $I(1)$ price series to the price discovery process: (1) the information share model (Hasbrouck, 1995); and (2) the common factor model (Gonzalo & Granger, 1995). Recent studies using at least one of these two approaches for cointegrated series includes Cabrera, Wang and Yang (2009), Chen and Gau (2009), Poskitt (2009), and Tao and Song (2010). Both models use an ECM as a basis, but differ in their perspectives of price discovery measurement.

Information Share Model If there exist $p-1$ cointegration relationships for a system with p $I(1)$ price variables, these p variables are driven by one common stochastic trend known as the implicit common efficient price (Baillie, Booth, Tse & Zabotina, 2002), which is driven by new information and thus serves as the source of permanent movements in all price series. The information share measures the price discovery contribution of a specific market by decomposing the innovation of the common efficient price into the innovation of the price of that market. In detail, we rewrite an ECM using a moving average representation: $\Delta X_t = e_t + \Psi_1 e_{t-1} + \Psi_2 e_{t-2} + \cdots$, where Ψ_i $(i = 1, 2, \ldots)$ is a $p \times p$ matrix and can be estimated following a unit innovation. The term $\Psi(1) \cdot e_t$, where $\Psi(1) = I_p + \Psi_1 + \Psi_2 + \cdots$, constitutes the long-run impact of an innovation on each of the price variables (Stock & Watson, 1988). For a p-variate system with $p-1$ cointegration relationships, matrix $\Psi(1)$ has identical rows (Hasbrouck, 1995). The variance of the common efficient price innovations can be expressed as: $\Psi\Omega\Psi^{'}$, where Ψ denotes the common row of matrix $\Psi(1)$, and Ω stands for the covariance matrix of the disturbance term from an ECM. The information share approach is thus performed through the decomposition of $\Psi\Omega\Psi^{'}$ into components associated with price innovations in all markets.

If innovations of different price variables are uncorrelated, i.e., the covariance matrix Ω of the disturbance term is diagonal, the information share of market j is given by:

$$IS_j = \frac{\psi_j^2 \Omega_{jj}}{\Psi\Omega\Psi'}, \tag{4}$$

where ψ_j is the j-th element of Ψ, and Ω_{jj} is the j-th diagonal element of Ω. Generally, innovations of different price variables are correlated, i.e., Ω is not diagonal, the information share is not unique, and upper

Based on the ECM in Equation (1), the hypothesis tested is whether $C_t - F_t$ characterizes $\beta' X_{t-1}$.

and lower bounds are constructed by orthogonalizing Ω (Hasbrouck, 1995). Let a lower triangular matrix F be the Cholesky factorization of Ω such that $\Omega = FF^{'}$, the information share of market j is given by:

$$IS_j = \frac{[(\Psi F)_j]^2}{\Psi \Omega \Psi'}, \tag{5}$$

where $(\Psi F)_j$ is the j-th element of ΨF. Since Cholesky factorization requires an ordering of the prices, the spread between the lower and upper bounds can be large, especially when innovations of different price variables are highly correlated. Baillie, Booth, Tse and Zabotina (2002) and many others provided evidence that the average information share can be used to identify price discovery contributions across markets.

Common Factor Model The common factor model assumes the aforementioned common efficient price to be a linear combination of the associated cointegrated price variables and focuses on the weight of each variable. Although the contemporaneous correlation is incorporated in the design of the information share model, it is not in that of the common factor model. In detail, the price vector X_t is decomposed into a permanent and a transitory component with the former being a function of the current values of X_t, observable as:

$$\underbrace{X_t}_{p\times 1} = \underbrace{A_1}_{p\times(p-r)} \underbrace{f_t}_{(p-r)\times 1} + \underbrace{A_2}_{p\times r} \underbrace{z_t}_{r\times 1}, \tag{6}$$

where $f_t \sim I(1)$ is the permanent component or the common efficient price, $z_t \sim I(0)$ is the transitory component, and $r = p - 1$. Two restrictions are imposed for the identification of the permanent component: (1) f_t is a linear combination of the current values of X_t, and (2) the transitory component has no permanent effect on X_t. Let the linear combination be $f_t = F_*^{'} X_t$, where $F_*^{'}$ is a $(p-r) \times p$ matrix orthogonal to the matrix of cointegrating vectors, α, in an ECM. Naturally, the elements of normalized F_* can be considered as measurements of contributions to price discovery of different price variables. Specifically, the contributions to price discovery of all markets are contained in vector ω given by:

$$\omega^{'} = \left\{ abs(F_*^{'}) \cdot \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}_{p\times 1} \right\}^{-1} abs(F_*^{'}), \tag{7}$$

where $abs(\cdot)$ stands for the operation of taking absolute values (Cabrera, Wang & Yang, 2009). We do not care about the signs of the elements of F_* since only their magnitudes provide price discovery contribution measurements.

2.2.3 Linear Granger Causality Test

Based on cases (b) and (c) of Equation (1), the null hypothesis of the linear Granger causality test is formulated as:

$$H_3\colon \Gamma_{i,12} = 0 \text{ or } \Gamma_{i,21} = 0 \text{ for } i = 1, ..., k-1, \tag{8}$$

where $\Gamma_{i,mn}$ represents the mn-th element of matrix Γ_i. Intuitively, if $\Gamma_{i,12} = 0$ ($\Gamma_{i,21} = 0$) for $i = 1, ..., k-1$ is rejected, but $\Gamma_{i,21} = 0$ ($\Gamma_{i,12} = 0$) for $i = 1, ..., k-1$ is not, then futures (cash) prices Granger cause cash (futures) prices unidirectionally from a linear perspective. If both $\Gamma_{i,12} = 0$ ($\Gamma_{i,12} \neq 0$) and $\Gamma_{i,21} = 0$ ($\Gamma_{i,21} \neq 0$) for $i = 1, ..., k-1$, then no (bidirectional) linear Granger causality exists between cash and futures prices. An ECM (A VAR in differences) is used to examine prices that are (not) cointegrated (Qiao, Li & Wong, 2008). For an ECM, this step does the short-run linear Granger causality test, and the long-run one is performed through the aforementioned prediction hypothesis test (Gurgul & Lach, 2012).

2.2.4 Nonlinear Granger Causality Test

One problem with the linear Granger causality test is that the common nonlinear relationships among variables are ignored (Shu & Zhang, 2012). Before the nonlinear Granger causality test, data nonlinearities are examined (Francis, Mougoué & Panchenko, 2010; Dergiades, Martinopoulos & Tsoulfidis, 2013) by applying the BDS test suggested by Broock, Scheinkman, Dechert and LeBaron (1996) to the residuals from an ECM or a VAR in differences (Dergiades, Martinopoulos & Tsoulfidis, 2013; Fujihara & Mougoué, 1997). The BDS test essentially inspects the validity of the identically and independently distributed (i.i.d) assumption on time series[6].

Shu and Zhang (2012), Francis, Mougoué and Panchenko (2010), Dergiades, Martinopoulos and Tsoulfidis (2013), Fujihara and Mougoué (1997), Silvapulle and Moosa (1999), Ajayi and Serletis (2009), and Dergiades (2012) gave a formal description of the nonlinear Granger causality test. The nonparametric nonlinear causal relationship testing method developed by Baek and Brock (1992) is modified by Hiemstra and Jones (1994) to investigate the causal relationships between stock prices and trading volumes. A brief introduction of the method is provided as follows.

Consider two strictly stationary and weakly dependent time series, $\{R_{1,t}\colon\ t = 1, ..., T\}$ and $\{R_{2,t}\colon\ t = 1, ..., T\}$. Let the $m-$length lead vector of $R_{1,t}$ be $R^m_{1,t}$, and the $l_{R_1}-$length and $l_{R_2}-$length lag vectors of $R_{1,t}$ and $R_{2,t}$ be $R^{l_{R_1}}_{1,t-l_{R_1}}$ and $R^{l_{R_2}}_{2,t-l_{R_2}}$, respectively. For given values of $m \geq 1$, $l_{R_1} \geq 1$, and $l_{R_2} \geq 1$, and an arbitrarily small constant $\epsilon > 0$, $R_{2,t}$ does not strictly nonlinearly Granger cause $R_{1,t}$ if:

[6] For a formal description of the BDS test, we can refer to Dergiades, Martinopoulos and Tsoulfidis (2013), and Fujihara and Mougoué (1997). For all technical details, we can refer to Broock, Scheinkman, Dechert and LeBaron (1996).

$$
\begin{aligned}
\Pr(||R_{1,t}^{m} - R_{1,s}^{m}|| &< \epsilon \mid ||R_{1,t-l_{R_1}}^{l_{R_1}} - R_{1,s-l_{R_1}}^{l_{R_1}}|| < \epsilon, ||R_{2,t-l_{R_2}}^{l_{R_2}} - R_{2,s-l_{R_2}}^{l_{R_2}}|| < \epsilon) \\
&= \Pr(||R_{1,t}^{m} - R_{1,s}^{m}|| < \epsilon \mid ||R_{1,t-l_{R_1}}^{l_{R_1}} - R_{1,s-l_{R_1}}^{l_{R_1}}|| < \epsilon), \qquad (9)
\end{aligned}
$$

where Pr stands for probability, $||\cdot||$ stands for maximum norm, and $s, t = \max(l_{R_1}, l_{R_2}) + 1, ..., T - m + 1$. The left hand side of Equation (9) is the conditional probability that two arbitrary $m-$length lead vectors of $R_{1,t}$ are within a distance ϵ of each other, given that the corresponding two $l_{R_1}-$length lag vectors of $R_{1,t}$ and two $l_{R_2}-$length lag vectors of $R_{2,t}$ are within a distance ϵ of each other. The right hand side of Equation (9) is the conditional probability that two arbitrary $m-$length lead vectors of $R_{1,t}$ are within a distance ϵ of each other, given that the corresponding two $l_{R_1}-$length lag vectors of $R_{1,t}$ are within a distance ϵ of each other. Equation (9) states that if $R_{2,t}$ does not strictly nonlinearly Granger cause $R_{1,t}$, then adding lagged values of $R_{2,t}$ does not improve the prediction power of $R_{1,t}$ from only $R_{1,t}$ lagged values. By representing the conditional probabilities in Equation (9) in terms of the corresponding ratios of joint probabilities, we have:

$$
\frac{C1(m + l_{R_1}, l_{R_2}, \epsilon)}{C2(l_{R_1}, l_{R_2}, \epsilon)} = \frac{C3(m + l_{R_1}, \epsilon)}{C4(l_{R_1}, \epsilon)}, \qquad (10)
$$

where

$$
\begin{aligned}
C1(m + l_{R_1}, l_{R_2}, \epsilon) &\equiv \Pr(||R_{1,t-l_{R_1}}^{m+l_{R_1}} - R_{1,s-l_{R_1}}^{m+l_{R_1}}|| < \epsilon, ||R_{2,t-l_{R_2}}^{l_{R_2}} - R_{2,s-l_{R_2}}^{l_{R_2}}|| < \epsilon), \qquad (11a) \\
C2(l_{R_1}, l_{R_2}, \epsilon) &\equiv \Pr(||R_{1,t-l_{R_1}}^{l_{R_1}} - R_{1,s-l_{R_1}}^{l_{R_1}}|| < \epsilon, ||R_{2,t-l_{R_2}}^{l_{R_2}} - R_{2,s-l_{R_2}}^{l_{R_2}}|| < \epsilon), \qquad (11b) \\
C3(m + l_{R_1}, \epsilon) &\equiv \Pr(||R_{1,t-l_{R_1}}^{m+l_{R_1}} - R_{1,s-l_{R_1}}^{m+l_{R_1}}|| < \epsilon), \qquad (11c) \\
C4(l_{R_1}, \epsilon) &\equiv \Pr(||R_{1,t-l_{R_1}}^{l_{R_1}} - R_{1,s-l_{R_1}}^{l_{R_1}}|| < \epsilon). \qquad (11d)
\end{aligned}
$$

The correlation-integral estimators of $C_j's$ in Equation (11a - 11d) are:

$$
\begin{aligned}
C1(m + l_{R_1}, l_{R_2}, \epsilon, n) &\equiv \frac{2}{n(n-1)} \sum_{t<s}\sum_{s} I(R_{1,t-l_{R_1}}^{m+l_{R_1}}, R_{1,s-l_{R_1}}^{m+l_{R_1}}, \epsilon) \times I(R_{2,t-l_{R_2}}^{l_{R_2}}, R_{2,s-l_{R_2}}^{l_{R_2}}, \epsilon), \qquad (12a) \\
C2(l_{R_1}, l_{R_2}, \epsilon, n) &\equiv \frac{2}{n(n-1)} \sum_{t<s}\sum_{s} I(R_{1,t-l_{R_1}}^{l_{R_1}}, R_{1,s-l_{R_1}}^{l_{R_1}}, \epsilon) \times I(R_{2,t-l_{R_2}}^{l_{R_2}}, R_{2,s-l_{R_2}}^{l_{R_2}}, \epsilon), \qquad (12b) \\
C3(m + l_{R_1}, \epsilon, n) &\equiv \frac{2}{n(n-1)} \sum_{t<s}\sum_{s} I(R_{1,t-l_{R_1}}^{m+l_{R_1}}, R_{1,s-l_{R_1}}^{m+l_{R_1}}, \epsilon), \qquad (12c) \\
C4(l_{R_1}, \epsilon, n) &\equiv \frac{2}{n(n-1)} \sum_{t<s}\sum_{s} I(R_{1,t-l_{R_1}}^{l_{R_1}}, R_{1,s-l_{R_1}}^{l_{R_1}}, \epsilon), \qquad (12d)
\end{aligned}
$$

where $n = T + 1 - m - \max(l_{R_1}, l_{R_2})$, and $I(\cdot)$ denotes a kernel that equals 1 when both vectors are within the maximum-norm distance ϵ of each other, and 0 otherwise. Using the joint probability estimators given in Equation (12a - 12d), the strict nonlinear Granger noncausality condition in Equation (9) can be tested as follows. For $m \geq 1$, $l_{R_1} \geq 1$, and $l_{R_2} \geq 1$, and an arbitrarily small constant $\epsilon > 0$, we have:

$$\sqrt{n}\left[\frac{C1(m+l_{R_1}, l_{R_2}, \epsilon, n)}{C2(l_{R_1}, l_{R_2}, \epsilon, n)} - \frac{C3(m+l_{R_1}, \epsilon, n)}{C4(l_{R_1}, \epsilon, n)}\right] \sim N(0, \sigma^2(m, l_{R_1}, l_{R_2}, \epsilon)), \tag{13}$$

where $\sigma^2(m, l_{R_1}, l_{R_2}, \epsilon)$ is the asymptotic variance of the modified Baek and Brock test statistic[7]. Under strict stationarity of $R_{1,t}$ and $R_{2,t}$, Equation (9) is actually a statement about the invariant distribution of the $(l_{R_1} + l_{R_2} + m)-$dimensional vector $(R_{1,t-l_{R_1}}^{l_{R1}}, R_{2,t-l_{R_2}}^{l_{R2}}, R_{1,t}^{m})$. If we let $m = l_{R_1} = l_{R_2} = 1$, Equation (9) can be represented as ratios of joint distributions of $(R_{1,t}, R_{2,t}, R_{1,t+1})$:

$$\frac{f_{r_{1,t},r_{2,t},r_{1,t+1}}(R_{1,t}, R_{2,t}, R_{1,t+1})}{f_{r_{1,t},r_{2,t}}(R_{1,t}, R_{2,t})} = \frac{f_{r_{1,t},r_{1,t+1}}(R_{1,t}, R_{1,t+1})}{f_{r_{1,t}}(R_{1,t})}. \tag{14}$$

The major drawback of Hiemstra and Jones test is that it tends to reject too often under the null of no nonlinear Granger causality, especially for small values of ϵ (Diks & Panchenko, 2005; Diks & Panchenko, 2006). A modified test statistic is introduced to address this issue by Diks and Panchenko (2006). Their restated null hypothesis is:

$$q \equiv E\left[f_{r_{1,t},r_{2,t},r_{1,t+1}}(R_{1,t}, R_{2,t}, R_{1,t+1}) f_{r_{1,t}}(R_{1,t}) - f_{r_{1,t},r_{2,t}}(R_{1,t}, R_{2,t}) f_{r_{1,t},r_{1,t+1}}(R_{1,t}, R_{1,t+1})\right] = 0. \tag{15}$$

And the modified test statistic is:

$$\begin{aligned} T_n(\epsilon) \quad = \quad & \frac{n-1}{n(n-2)} \sum_{i}^{n} [\hat{f}_{r_{1,t},r_{2,t},r_{1,t+1}}(r_{1,it}, r_{2,it}, r_{1,it+1}) \hat{f}_{r_{1,t}}(r_{1,it}) \\ & - \hat{f}_{r_{1,t},r_{2,t}}(r_{1,it}, r_{2,it}) \hat{f}_{r_{1,t},r_{1,t+1}}(r_{1,it}, r_{1,it+1})]. \end{aligned} \tag{16}$$

The local density estimator of each d_z-variate random vector Z at z_i is expressed as:

$$\hat{f}_z(z_i) = \frac{(2\epsilon)^{-d_z}}{n-1} \sum_{j, j \neq i} I(z_i, z_j, \epsilon) \text{ for } z_i = R_{1,it}, R_{2,it}, R_{1,it+1}. \tag{17}$$

Diks and Panchenko (2006) showed that, for $l_{R_1} = l_{R_2} = 1$, if the sequence of bandwidth values is determined by $\epsilon_n = Cn^{-\beta}$ for any $C > 0$ and $\beta \in (1/4, 1/3)$, $T_n(\epsilon)$ converges to a standard normal distribution:

$$\sqrt{n}\frac{[T_n(\epsilon) - q]}{S_n} \xrightarrow{D} N(0, 1), \tag{18}$$

where S_n is the estimated standard error of $T_n(\cdot)$. The test statistic in Equation (18) is applied to the residuals from an ECM or a VAR in differences.

[7] See the appendix in Hiemstra and Jones (1994) for a detailed derivation of the variance.

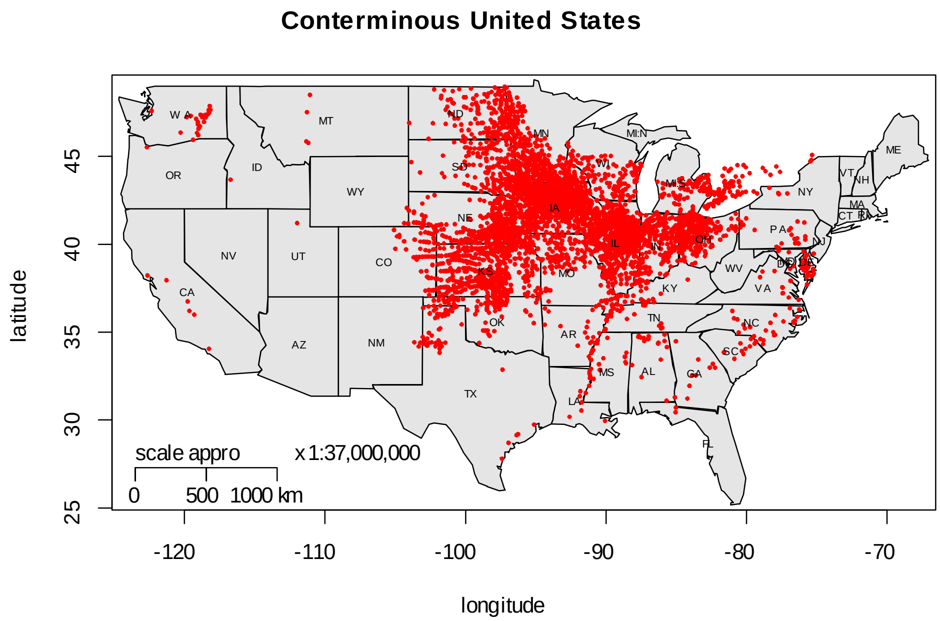

Figure 1: All Cash Markets with Available Data and Location Information

3 Data

An unbalanced panel of daily corn cash price data obtained from GeoGrain Inc. includes over 4,000 markets and covers a 7-year period from September 2005 to March 2011, totaling more than 3.5 million observations. Figure 1 plots the universe of markets with available data and location information. To select markets with the largest numbers of observations, Figure 2 illustrates the 182 markets (indexed as market 1 to 182) used in this study. On days such as holidays where prices are missing in each market, we omit the observations and assume a smooth continuity of prices (Goodwin & Piggott, 2001) as if the missing data does not appear. Other missing prices are approximated by cubic spline interpolation. The percentage of missing observations ranges from 0.3% to 5.24% of the whole sample across markets, which covers a 6-year period from January 2006 to March 2011, totaling 1316 observations for each market. Futures prices of the nearest maturity contracts are also provided by GeoGrain Inc. For the rest of this study, prices are converted to their natural logarithms. Figure 3 plots the price series of the futures and all of the 182 cash markets. As one might have expected, these price series are very close to each other. The correlation coefficient between the price series of the futures market and that of a cash market ranges from 0.9879 to 0.9972. The unit root test results show that all of the price series are not stationary in levels but stationary in differences at the 5% significance level[8].

[8]Detailed numerical results are available upon request.

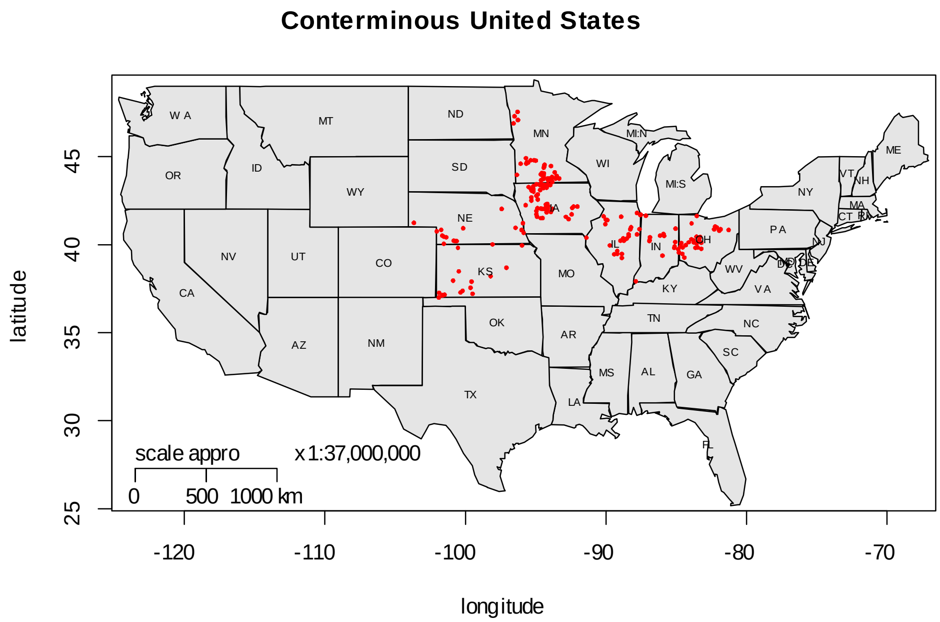

Figure 2: The 182 Cash Markets

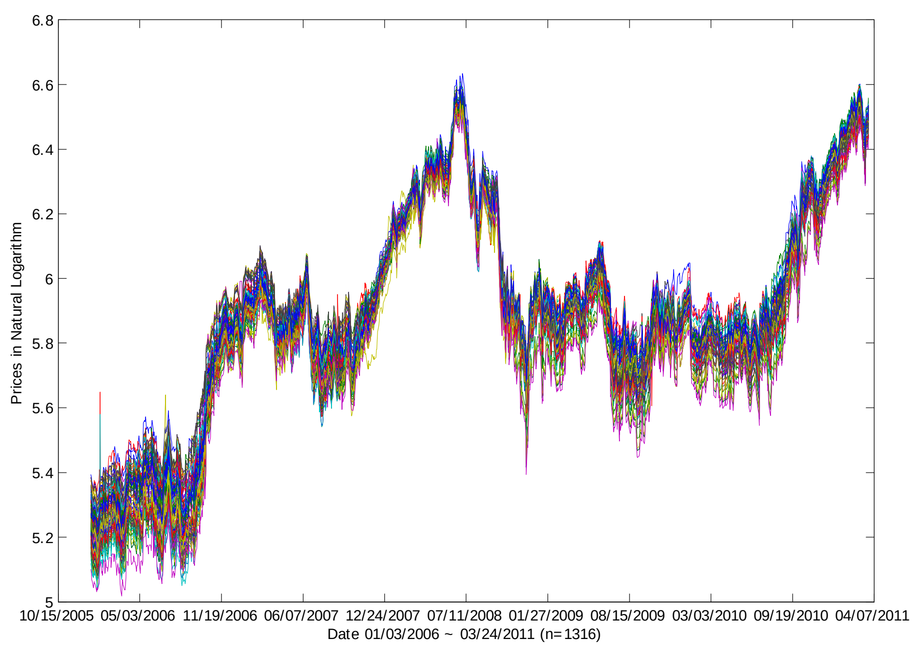

Figure 3: Price Series of the Futures and All of the 182 Cash Markets

4 Empirical Results

Empirical results are listed in Table 1 - 2[9]. The optimal number of lags of an ECM or a VAR in differences is selected by Bayesian Information Criterion (BIC). The nonlinearities of the residuals from an ECM or a VAR in differences are decided based on the significance of the BDS statistics, which indicates the appropriateness of the nonlinear causality testing (Dergiades, Martinopoulos & Tsoulfidis, 2013). For the Diks-Panchenko nonlinear Granger causality test, we present results for lags $l_{R_1} = l_{R_2} = 1$. The constant C in the bandwidth ϵ_n is set at 7.5 (Bekiros & Diks, 2008a; Bekiros & Diks, 2008b), close to the value 8 for ARCH processes (Diks & Panchenko, 2006). The β in the bandwidth ϵ_n is set at $\frac{2}{7}$ (Bekiros & Diks, 2008a; Bekiros & Diks, 2008b), its theoretical optimal value (Diks & Panchenko, 2006). As a result, the bandwidth ϵ_n is set at 1 approximately. Generally, a larger (smaller) p value can be expected with a smaller (larger) bandwidth (Bekiros & Diks, 2008a; Bekiros & Diks, 2008b).

Among the 182 cash markets we investigate, 130 (71.43%) of them are not cointegrated and 52 (28.57%) of them are cointegrated with the futures market[10]. We plot the cash markets (not) cointegrated with the futures market using blue (red) points in Figure 4. Meanwhile, in Figure 5, price series of the futures market, a cash market cointegrated with the futures market, and a cash market not cointegrated with the futures market are plotted to show a typical cash market (not) cointegrated with the futures market. The explicit relationship among a cash market, the company (indexed as C1 to C60) it belongs to, and the existence of cointegration with the futures market is listed in Table 3. It shows that 29 (43.94%) companies own cash markets cointegrated with the futures market, and the other 37 (56.06%) do not. Since several companies (marked with a yellow background in Table 3) own cash markets cointegrated and not cointegrated with the futures market within a specific state, and several companies (marked with a red background in Table 3) own cash markets cointegrated and not cointegrated with the futures market both within a state and across states, there exist some overlaps in counting the number of the companies. If we remove these companies (C3, C4, C11, C14, C15, and C43), among the remaining 54 companies, 23 (42.59%) of them own cash markets cointegrated with the futures market, and the other 31 (57.41%) do not. We also analyze the cointegration relationship (or lack thereof) between a cash market and the futures market for each state based on both cash markets and the companies owning them (see Table 4). Unlike the other six states (IA, IN, OH, MN, KS, and NE) where the number of the cash markets which are cointegrated with the futures market is smaller than that of the cash markets which are not[11], IL has 23 cash markets all cointegrated with the futures market. Actually, these 23 cash markets in IL alone contribute to almost half of the 52 cointegration relationships found in this study with the contribution ratio being 23/52 (44.23%). If the cointegration relationships are

[9] Some detailed numerical results not presented are available upon request.

[10] All tests in Table 1 - 2 are performed at the 5% significance level.

[11] IN is an exception since it has 8 cash markets that are cointegrated with the futures market and 7 cash markets that are not.

Table 1: Cash Markets not Cointegrated with the Futures Market, Cointegration Rank = 0 (VAR in Differences)

Market	RCT[1]	LGC[2]	NLGC[3]
1-26 (IA), 43-47 (IN), 51-56 (KS), 66-77 (MN), 97 (NE), 101-107 (NE), 111-124 (OH), 126-128 (OH)	Y	C→F	N
27-37 (IA), 57-62 (KS), 96(NE), 98-100 (NE), 125 (OH)	Y	N	N
38-41 (IA), 93 (MN), 108-109 (OH)	S	C→F	N
42 (IA), 78-88 (MN)	Y	C↔F	N
48 (IN)	Y	F→C	C↔F
49 (IN)	S	C→F	C↔F
95 (NE)	S	N	N
63-64 (KS), 89-91 (MN), 110 (OH)	Y	C→F	C→F
65 (MN)	Y	C→F	F→C
92 (MN)	S	C↔F	N
94 (MN)	S	C→F	C→F
50 (KS), 129 (OH)	S	F→C	N
130 (OH)	Y	F→C	F→C

[1] Recursive cointegration test: Y for stability of the lack of a cointegration relationship, and S for existence of some structural breaks in the lack of a cointegration relationship.

[2] Linear Granger causality test: C for cash prices, F for futures prices, → for unidirectional linear Granger causality, ↔ for bidirectional linear Granger causality, and N for no linear Granger causality.

[3] Nonlinear Granger causality test: C for cash prices, F for futures prices, → for unidirectional nonlinear Granger causality, ↔ for bidirectional nonlinear Granger causality, and N for no nonlinear Granger causality. For all cash markets, nonlinearities of the residuals from the VAR in differences are confirmed by the BDS statistics.

[4] All tests are performed at the 5% significance level.

Table 2: Cash Markets Cointegrated with the Futures Market, Cointegration Rank = 1 (ECM)

Market	RCT[1]	$H_{2,joint}$[2]	PHT[3]	AIS_c[4]	CFW_c[5]	LGC[6]	NLGC[7]
131 (IA)	Y	R	F↔C	0.4927	0.4247	C→F	N
132 (IA)	Y	R	F↔C	0.4404	0.1949	C→F	F→C
133 (IA)	Y	F	F↔C	0.4878	0.4343	N	N
134 (IA)	Y	R	F↔C	0.4577	0.2015	C→F	N
135 (IA)	Y	R	F↔C	0.5141	0.5629	C→F	N
136 (IA)	Y	R	F↔C	0.5084	0.5246	C→F	N
137 (IA)	Y	R	F↔C	0.4580	0.1691	C→F	C→F
138 (IA)	Y	R	F↔C	0.4758	0.3109	C→F	N
139 (IN)	Y	F	F↔C	0.5811	0.9377	C→F	N
140 (IN)	Y	F	F↔C	0.5456	0.7477	C→F	F→C
141 (IN)	Y	F	F↔C	0.4617	0.1372	C→F	N
142 (IN)	Y	F	F↔C	0.5539	0.7749	C→F	N
143 (IN)	Y	R	F↔C	0.6203	0.7969	C→F	N
144 (IN)	Y	F	F↔C	0.4235	0.1343	N	N
145 (IN)	Y	F	F↔C	0.4026	0.2041	N	N
146 (IN)	Y	R	F↔C	0.5260	0.7075	C→F	N
147 (IL)	Y	F	F↔C	0.4609	0.3587	F↔C	F→C
148 (IL)	Y	R	F↔C	0.5016	0.4917	F↔C	F→C
149 (IL)	Y	F	F↔C	0.5172	0.7271	C→F	N
150 (IL)	Y	R	F↔C	0.6160	0.7742	C→F	F→C
151 (IL)	Y	R	C→F	0.6137	0.7560	C→F	F→C
152 (IL)	Y	R	C→F	0.6183	0.7440	C→F	N
153 (IL)	Y	F	F↔C	0.5030	0.5192	C→F	N
154 (IL)	Y	R	F↔C	0.5438	0.9314	C→F	N
155 (IL)	Y	F	F↔C	0.5204	0.7608	C→F	N
156 (IL)	Y	F	F↔C	0.5229	0.7857	C→F	N
157 (IL)	Y	R	F↔C	0.6039	0.7818	C→F	N
158 (IL)	Y	R	F↔C	0.5728	0.9997	N	N
159 (IL)	Y	F	F↔C	0.4418	0.2259	C→F	N
160 (IL)	Y	R	C→F	0.6439	0.7429	C→F	C→F
161 (IL)	Y	F	F↔C	0.5374	0.7384	C→F	N

Market	RCT[1]	$H_{2,joint}$[2]	PHT[3]	AIS_c[4]	CFW_c[5]	LGC[6]	NLGC[7]
162 (IL)	Y	R	F↔C	0.6134	0.7300	C→F	N
163 (IL)	Y	R	F↔C	0.5078	0.5623	C→F	N
164 (IL)	Y	R	F↔C	0.5367	0.7441	C→F	N
165 (IL)	Y	F	F↔C	0.3981	0.2223	C→F	N
166 (IL)	Y	R	F↔C	0.5718	0.8671	C→F	N
167 (IL)	Y	F	F↔C	0.5161	0.5901	C→F	N
168 (IL)	Y	F	F↔C	0.5489	0.9076	F↔C	F→C
169 (IL)	Y	F	F↔C	0.4423	0.2380	C→F	F→C
170 (OH)	Y	F	F↔C	0.5379	0.7268	C→F	N
171 (OH)	Y	F	F↔C	0.5415	0.7501	C→F	N
172 (OH)	Y	F	F↔C	0.4501	0.1527	C→F	N
173 (OH)	Y	F	F↔C	0.5003	0.4863	C→F	N
174 (MN)	Y	R	F↔C	0.4417	0.1569	C→F	N
175 (MN)	Y	R	F↔C	0.4389	0.1701	C→F	N
176 (MN)	Y	R	F↔C	0.4283	0.2556	F→C	C→F
177 (MN)	Y	R	F↔C	0.4398	0.1509	C→F	N
178 (MN)	Y	R	F↔C	0.4315	0.1291	C→F	N
179 (KS)	Y	R	F↔C	0.4964	0.4393	F↔C	F→C
180 (NE)	Y	R	F↔C	0.4979	0.4644	C→F	N
181 (NE)	Y	R	F↔C	0.5095	0.5484	C→F	N
182 (NE)	Y	F	F↔C	0.4785	0.2339	N	N

[1] Recursive cointegration test: Y for stability of the cointegration relationship, and S for existence of some structural breaks in the cointegration relationship.

[2] F for failure to reject the null hypothesis, and R for rejecting the null hypothesis.

[3] Prediction hypothesis test: C for cash prices, F for futures prices, → for unidirectional information flow, and ↔ for bidirectional information flow.

[4] The average information share of a cash market. Results are rounded to 4 decimal places. The average information share of the futures market$= 1 - AIS_c$.

[5] The common factor weight of a cash market. Results are rounded to 4 decimal places. The common factor weight of the futures market$= 1 - CFW_c$.

[6] Linear Granger causality test: C for cash prices, F for futures prices, → for unidirectional linear Granger causality, ↔ for bidirectional linear Granger causality, and N for no linear Granger causality.

[7] Nonlinear Granger causality test: C for cash prices, F for futures prices, → for unidirectional nonlinear Granger causality, ↔ for bidirectional nonlinear Granger causality, and N for no nonlinear Granger causality. For all cash markets, nonlinearities of the residuals from the ECM are confirmed by the BDS statistics.

[8] All tests are performed at the 5% significance level.

counted based on companies, the 13 companies in IL alone still have a contribution ratio that is almost 50%, i.e. 13/29 (44.83%). Since IL River delivery facilities provide adequate commercial flows of corns for the delivery process (Irwin, Garcia, Good & Kunda, 2011), the cash markets in IL are closely related to the futures market. The high contribution ratios are thus to be expected. Furthermore, the numerical results in Table 4 are visualized qualitatively in Figure 6. For a specific state (IA, IN, OH, MN, KS, or NE), the ratio of cash markets in it which are cointegrated with the futures market and that of companies in it owning cash markets cointegrated with the futures market decrease as its distance to IL increases[12]. In sum, we show that the selection of cash markets affects cointegration between cash and futures markets. This result confirms Goodwin and Schroeder's (1991) work which stated that market volumes and types are two significant factors influencing cointegration, and extends their conclusion from the case of regional cash markets to our case of cash and futures markets. Meanwhile, our result supports Schroeder's (1997) statement that plant level prices, instead of Agricultural Marketing Service ones, are the most relevant price data for market performance analysis since the lack of cointegration between U.S. corn cash and futures markets is not found in recent studies using aggregate cash price data. For the stability of the cointegration relationship (or lack thereof), the recursive cointegration test shows no structural breaks for 169 cash markets and some structural breaks (less than 15% of the whole sample) for the remaining 13 which all belong to those not cointegrated with the futures market. Since most cointegration relationships (or lack thereof) are stable, it is highly possible that the structural breaks are due to idiosyncratic reasons based on the selection of cash markets, such as tentative new pricing policies and temporary changes in demand and supply for a specific cash market.

For the 130 cash markets not cointegrated with the futures market, both the linear and nonlinear Granger causality tests present mixed results. For the linear Granger causality test, 90 cash markets show causal relationships from the cash market to the futures market, 4 reveal the inverse, 13 indicate bidirectional and 23 find no causality. The existence of the vast majority of unidirectional causality from the cash market to the futures market and bidirectional causality between them, and an extra small ratio of unidirectional causality from the futures market to the cash market, is because many cash markets not cointegrated with the futures market are operated by big local companies at non-delivery points, whose prices, which incorporate information from the futures market to some extent, are largely determined by local supply and demand, and these market conditions as a whole affect futures prices. The reason for the lack of linear causality between the cash market and the futures market for the remaining 23 cash markets is that adding lagged cash prices does not improve the prediction power of the futures prices from only lagged futures prices and vise visa based on the 5% significance level. Schroeder's (1997) statement is further enhanced since these results are not discovered in previous studies using aggregate data. In the first three columns of Figure 7, coefficients $\Gamma_{1,12}$

[12] One exception exists for IA and NE as marked in yellow background in Table 4.

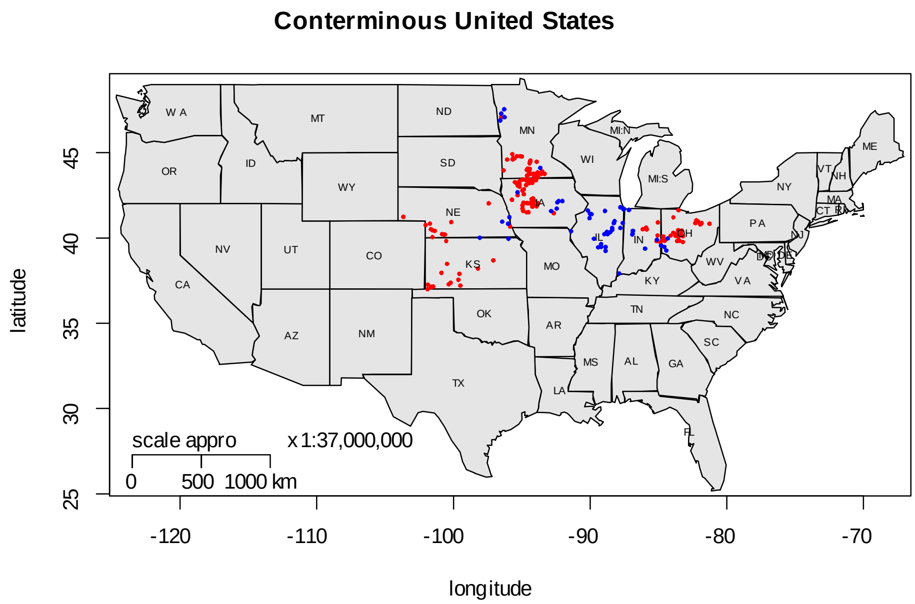

Figure 4: Cash Markets Cointegrated (in Blue) and not Cointegrated (in Red) with the Futures Market

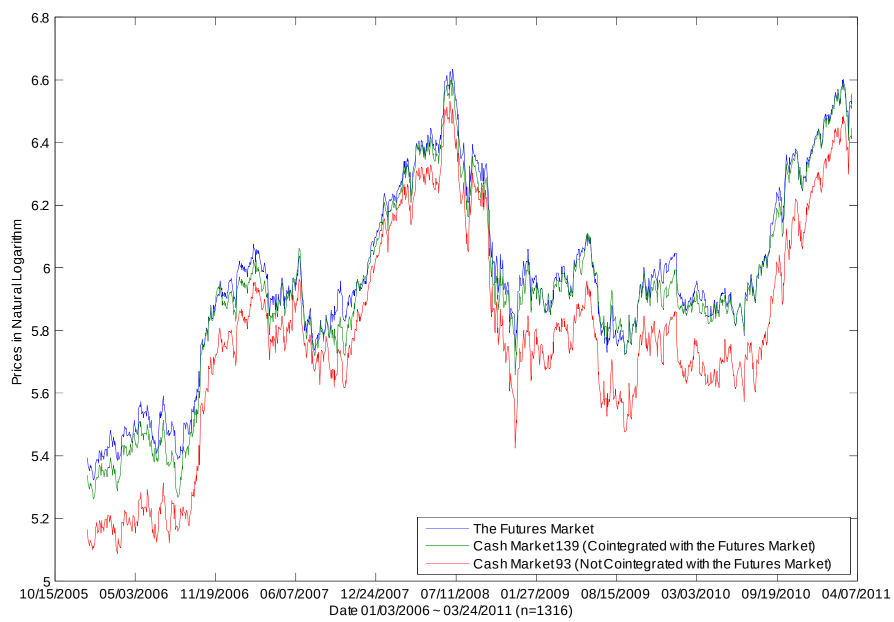

Figure 5: Price Series of the Futures Market, Cash Market 139 Cointegrated with the Futures Market, and Cash Market 93 not Cointegrated with the Futures Market

Table 3: The Relationship among a Cash Market, the Company It belongs to, and the Existence of Cointegration with the Futures Market

State	Cash Market not Cointegrated with the Futures Market	Company Index	Cash Market Cointegrated with the Futures Market	Comany Index
IA	1-17	C1	131-132, 136	C9
	18, 36	C2	133	C10
	19	C3	134	C3
	20, 38-41	C4	135	C4
	21-26	C5	137	C11
	27-35	C6	138	C12
	37	C7		
	42	C8		
IN	43-44, 48	C14	140	C14
	45-46	C15	141, 146	C15
	47	C16	144	C17
	49	C11	142-143, 145	C11
			139	C13
IL			147-148	C18
			149, 153-156	C19
			150-152	C20
			157	C21
			158	C22
			159	C23
			160	C24
			161	C25
			162	C26
			163	C27
			164, 166-168	C13
			165	C28
			169	C29
OH	108-117, 124	C30	172	C36
	118	C31	173	C37
	119-121	C14	170-171	C14
	122-123, 126-128	C32		

State	Cash Market not Cointegrated with the Futures Market	Company Index	Cash Market Cointegrated with the Futures Market	Comany Index
OH	125	C33		
	129	C34		
	130	C35		
MN	65-68	C38		
	69	C11		
	70, 76-77	C39		
	71-75, 80-88	C8		
	78-79	C40		
	89-91, 94	C41		
	92	C42	176	C44
	93	C43	174-175, 177-178	C43
KS	50	C45	179	C54
	51	C46		
	52	C47		
	53	C48		
	54	C49		
	55, 62	C50		
	56	C51		
	57-61	C52		
	63-64	C53		
NE	95-96, 98-102, 104, 106~107	C55	180-181	C59
	97	C56	182	C60
	103	C57		
	105	C58		

Table 4: Analysis of the Cointegration Relationship (or Lack thereof) between a Cash Market and the Futures Market for Each State

State	Based on Cash Markets		Based on Companies	
	Not Cointegrated[1]	Cointegrated[2]	Not Cointegrated[3]	Cointegrated[4]
IA	42 (84.00%)	8 (16.00%)	8 (57.14%)	6 (42.86%)[5]
			6 (60.00%)	4 (40.00%)[6]
IN	7 (46.67%)	8 (53.33%)	4 (44.44%)	5 (55.56%)
			1 (33.33%)	2 (66.67%)
IL	0 (0.00%)	23 (100.00%)	0 (0.00%)	13 (100.00%)
			0 (0.00%)	13 (100.00%)
OH	23 (85.19%)	4 (14.81%)	7 (70.00%)	3 (30.00%)
			6 (75.00%)	2 (25.00%)
MN	30 (85.71%)	5 (14.29%)	8 (80.00%)	2 (20.00%)
			7 (87.50%)	1 (12.50%)
KS	15 (93.75%)	1 (6.25%)	9 (90.00%)	1 (10.00%)
			9 (90.00%)	1 (10.00%)
NE	13 (81.25%)	3 (18.75%)	4 (66.67%)	2 (33.33%)
			4 (66.67%)	2 (33.33%)

[1] The number (ratio) of cash markets in each state which are not cointegrated with the futures market.

[2] The number (ratio) of cash markets in each state which are cointegrated with the futures market.

[3] The number (ratio) of companies in each state owning cash markets not cointegrated with the futures market.

[4] The number (ratio) of companies in each state owning cash markets cointegrated with the futures market.

[5] Overlaps in counting the number of the companies are not adjusted in this row.

[6] Overlaps in counting the number of the companies are adjusted in this row by removing the companies owning cash markets cointegrated and not cointegrated with the futures market for each state.

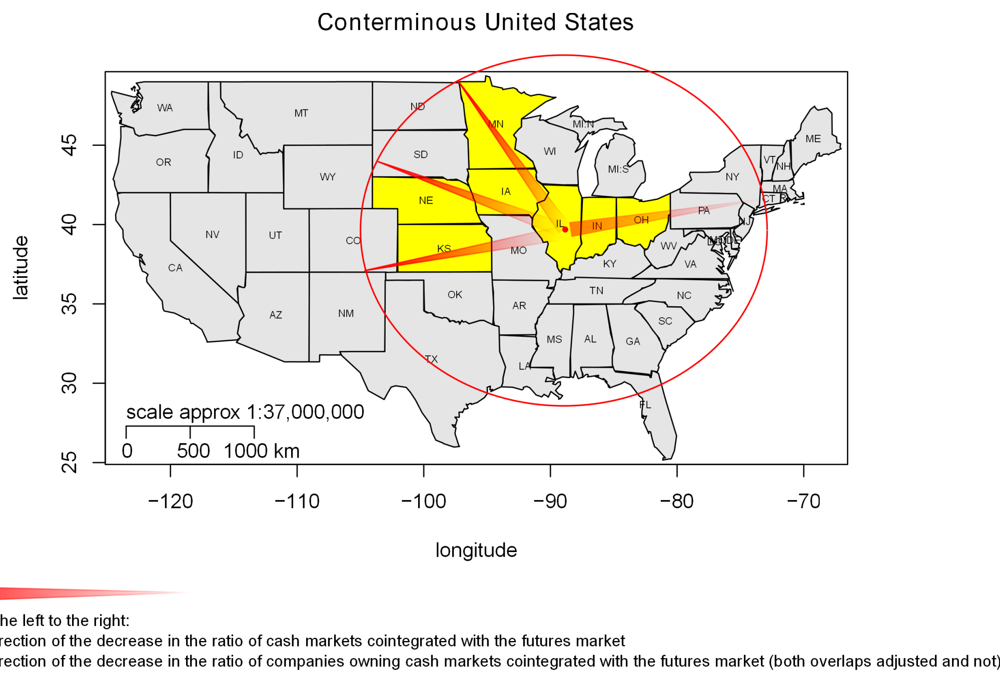

Figure 6: Qualitative Visualization of Numerical Results in Table 4

and $\Gamma_{1,21}$ are plotted for a better understanding of the linear Granger causality test results[13]. Obviously, when the price series of a cash market linearly Granger causes that of the futures market but not the inverse, the coefficients of lagged cash prices in the futures equation, $\Gamma_{i,21}$'s, will be relatively large but those of lagged futures prices in the cash equation, $\Gamma_{i,12}$'s, will be relatively small, and vise verse. And when there exists bidirectional (no) causality between the price series of a cash and the futures market, the coefficients of lagged cash prices in the futures equation, $\Gamma_{i,21}$'s, and those of lagged futures prices in the cash equation, $\Gamma_{i,12}$'s, will be relatively large (small) at the same time. For the nonlinear Granger causality test, 7 cash markets show causal relationships from the cash market to the futures market, 2 reveal the inverse, 2 indicate bidirectional and 119 find no causality. Hence, the causal relationships between most cash markets and the futures market are linear, even nonlinearities of the residuals from a VAR in differences are confirmed by the BDS test for all cash markets. For the aforementioned 23 cash markets which show no linear causality with the futures market, no nonlinear causality with the futures market is discovered either. We also find that:

[13] Coefficients $\Gamma_{i,12}$'s and $\Gamma_{i,21}$'s associated with cash markets 48, 50, 56, 103, 129, and 130 are not plotted in Figure 7. The optimal numbers of lags corresponding to these six markets are 3, 4, 3, 4, 4, and 2, respectively in VAR in levels representation. $\Gamma_{1,12} = 0.467$, $\Gamma_{2,12} = 0.154$, $\Gamma_{1,21} = 0.0595$, and $\Gamma_{2,21} = 0.0201$ for market 48; $\Gamma_{1,12} = 0.544$, $\Gamma_{2,12} = 0.305$, $\Gamma_{3,12} = 0.148$, $\Gamma_{1,21} = 0.0941$, $\Gamma_{2,21} = 0.0346$, and $\Gamma_{3,21} = 0.0253$ for market 50; $\Gamma_{1,12} = -0.00555$, $\Gamma_{2,12} = 0.0426$, $\Gamma_{1,21} = 0.192$, and $\Gamma_{2,21} = 0.0813$ for market 56; $\Gamma_{1,12} = -0.0175$, $\Gamma_{2,12} = 0.0327$, $\Gamma_{3,12} = -0.0973$, $\Gamma_{1,21} = 0.337$, $\Gamma_{2,21} = 0.0738$, and $\Gamma_{3,21} = 0.192$ for market 103; $\Gamma_{1,12} = -0.0992$, $\Gamma_{2,12} = 0.0729$, $\Gamma_{3,12} = 0.211$, $\Gamma_{1,21} = 0.0544$, $\Gamma_{2,21} = -0.0109$, and $\Gamma_{3,21} = -0.000210$ for market 129; $\Gamma_{1,12} = 0.165$, and $\Gamma_{1,21} = 0.0937$ for market 130.

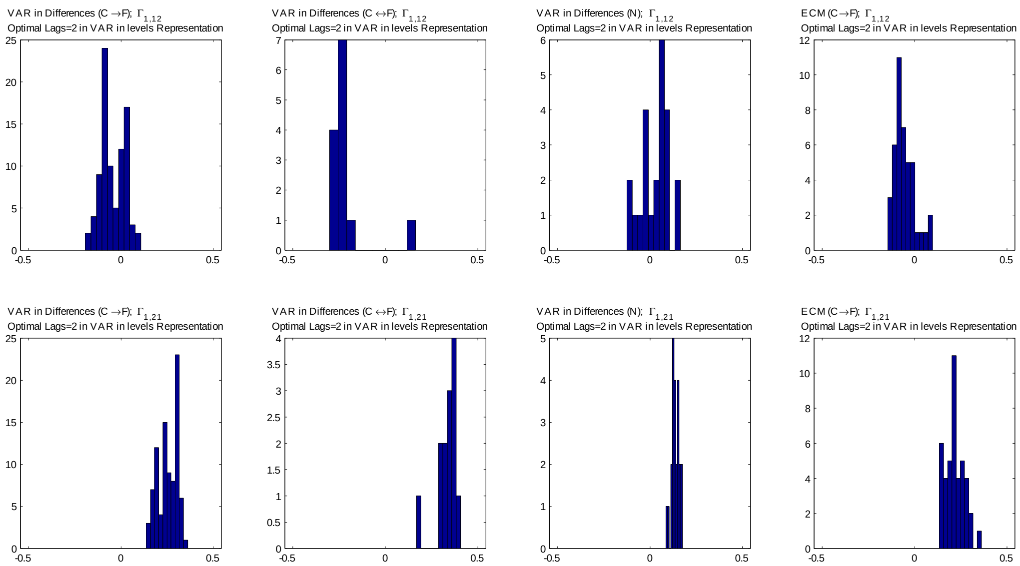

Figure 7: Histograms of Coefficients $\Gamma_{1,12}$ and $\Gamma_{1,21}$

(a) the nonlinear Granger causality test may enhance the result of the linear one (see markets 63, 64, 89, 90, 91, 94, 110, and 130); (b) the nonlinear Granger causality test may result in a different conclusion from that of the linear one (see markets 49 and 65). These two cases have been found in previous literature (e.g., Bekiros & Diks, 2008a, 2008b; Fujihara & Mougoué, 1997; Nazlioglu, 2011; Shu & Zhang, 2012; Silvapulle & Moosa, 1999).

For the 52 cash markets cointegrated with the futures market, model $H_1^*(1)$ is adopted. Results of the prediction hypothesis test, the linear and nonlinear Granger causality tests, the information share and the common factor weight are all mixed. Yang, Bessler and Leatham (2001) found that futures prices are the primary informational sources of cash prices in the long run for corn. However, in this study, 3 cash markets show unidirectional long-run causal relationships from the cash market to the futures market, and 49 reveal bidirectional causality based on the results of the prediction hypothesis test. Thus, the informational source roles of futures and cash prices are generally equal in the long run. This result is consistent with Yang, Bessler and Leatham (2001) when they examined the prediction hypothesis for pork bellies and hog between January 1, 1992 and March 31, 1996, and Minneapolis Grain Exchange wheat, cotton and feeder cattle between April 1, 1996 and June 30, 1998. For the linear Granger causality test, 1 cash market shows a causal relationship from the futures market to the cash market, 42 reveal the inverse, 4 indicate bidirectional and 5 find no causality. These results are similar to those of the cash markets not cointegrated with the futures market. As what we do for cash markets not cointegrated with the futures market, coefficients $\Gamma_{1,12}$

and $\Gamma_{1,21}$ are plotted in the last column of Figure 7[14]. Using weekly data for year 1994-2009, Hernandez and Torero (2010) found that, for lags up to 10, corn futures returns Granger cause spot returns for all lags, but the inverse causality only happens for lags 1, 7 and 8 based on the 5% significance level. They also conducted the linear Granger causality test by segmenting the whole sample based on both two-year periods and U.S. farm programs (1990, 1996, 2002, and 2008 Farm Bills), and showed that, generally, the linear Granger causality from the futures market to the cash market still holds, but the inverse does not. Hence, cash market selection and the corresponding data frequency may affect the linear Granger causality test results. For the nonlinear Granger causality test, Hernandez and Torero (2010) pointed out that, for lags $l_{R_1} = l_{R_2} = 1$, there exist bidirectional information flows between the futures market and the cash market, which are not discovered in this study. While for 40 of the 52 cash markets, we find no nonlinear Granger causal relationships with the futures market, 3 show unidirectional nonlinear causality from the cash market to the futures market, and 9 reveal the inverse. Similar to the cash markets not cointegrated with the futures market, the vast majority of causal relationships are linear. For the relative contributions to price discovery, the lower and upper bounds of the information share differ largely due to the strong correlation between the residuals from an ECM. As suggested by Baillie, Booth, Tse and Zabotina (2002), the mean of the lower and upper bounds is used to identify price discovery contributions across markets. Qualitatively, the common factor weight and the information share average draw the same conclusion about the relative contributions of the futures market and a specific cash market to the price discovery process[15]: the former (latter) finds that the contribution of the futures market is smaller for 30 (28) cash markets. This empirical result is also found in Tao and Song's (2010) work which investigated the Hong Kong Hang Seng index markets, and Theissen's (2002) work which examined floor and screen trading systems in Germany. Quantitatively, however, these two methods differ considerably in numerical results for most cash markets[16]. As pointed out by Baillie, Booth, Tse and Zabotina (2002), we are not indicating that one method is better than another since they differ in the perspective of price discovery and have their own merits (de Jong, 2002). Nonetheless, it is worth

[14] Coefficients $\Gamma_{i,12}$'s and $\Gamma_{i,21}$'s associated with cash markets 133, 144, 145, 147, 148, 158, 168, 176, 179, and 182 are not plotted in Figure 7. The optimal numbers of lags corresponding to these ten markets are 4, 2, 2, 3, 3, 2, 2, 3, 2, and 2, respectively in VAR in levels representation. $\Gamma_{1,12} = -0.0637$, $\Gamma_{2,12} = 0.0310$, $\Gamma_{3,12} = 0.0916$, $\Gamma_{1,21} = 0.00901$, $\Gamma_{2,21} = -0.0665$, and $\Gamma_{3,21} = 0.0794$ for market 133; $\Gamma_{1,12} = -0.120$, and $\Gamma_{1,21} = 0.0889$ for market 144; $\Gamma_{1,12} = 0.0972$, and $\Gamma_{1,21} = 0.0895$ for market 145; $\Gamma_{1,12} = 0.321$, $\Gamma_{2,12} = 0.149$, $\Gamma_{1,21} = 0.169$, and $\Gamma_{2,21} = 0.0109$ for market 147; $\Gamma_{1,12} = 0.350$, $\Gamma_{2,12} = 0.145$, $\Gamma_{1,21} = 0.121$, and $\Gamma_{2,21} = -0.0212$ for market 148; $\Gamma_{1,12} = 0.0313$, and $\Gamma_{1,21} = 0.121$ for market 158; $\Gamma_{1,12} = -0.247$, and $\Gamma_{1,21} = 0.306$ for market 168; $\Gamma_{1,12} = 0.507$, $\Gamma_{2,12} = 0.209$, $\Gamma_{1,21} = 0.0637$, and $\Gamma_{2,21} = 0.00820$ for market 176; $\Gamma_{1,12} = -0.103$, and $\Gamma_{1,21} = 0.128$ for market 179; $\Gamma_{1,12} = -0.0571$, and $\Gamma_{1,21} = 0.167$ for market 182.

[15] Two exceptions are cash markets 148 and 173 for which the information share average finds that the cash market contributions more to the price discovery process while the common factor weight reveals an opposite result. However, the numerical results provided by the two approaches are almost identical for each of these two cash markets.

[16] For cash markets 131, 133, 135, 136, 153, 160, 163, 167, 179, 180, and 181, the absolute values of the differences are smaller than 0.1.

mentioning that the absolute value of the difference of the relative contributions of the futures market and a specific cash market to the price discovery process is larger under the common factor weight than that under the information share average.

5 Conclusions

With a special attention paid to the role of cash market selection, this study examines dynamic relationships between U.S. corn cash and futures prices for 182 cash markets spreading across 7 states from January 2006 to March 2011. To explore whether the long-standing empirical results of cointegration between cash and futures prices and price discovery in the futures market are robust to the selection of cash markets, we apply an ECM or a VAR in differences to our observational data, and investigate how results of various statistical tests associated with price discovery research change with different cash markets selected for analysis.

First, the prevalent cointegration relationship between corn cash and futures prices only holds for 52 cash markets based on logarithmic prices at the 5% significance level. Although neglect of cointegration between cash and futures prices, if it does exist, leads to an underestimate of hedge ratios and affects hedge performance (Kroner & Sultan, 1993), our result shows that whether it is necessary to take cointegration into consideration is cash market dependent. Meanwhile, for the whole sample period in this study, structural breaks only have minor effects on the stability of the lack of cointegration for 13 cash markets. Hence, any further conclusion is not seriously affected without breaking the whole sample period into subperiods for these 13 cash markets.

Second, the informational source roles of futures and cash prices are equal in the long run for 49 out of the 52 cash markets cointegrated with the futures market based on the prediction hypothesis test. We fail to detect futures prices being the sole primary information source in the long run for all the 52 cash markets. Hence, plant level cash price data in this study shows that cash prices are useful in providing price movement information in the long run.

Third, although causal flows may not exist between cash and futures prices in the short run, the unidirectional causality from cash to futures prices is most possible if short-run causal flows exist no matter whether the cash market is cointegrated with the futures market or not. From a linear perspective, the plant level cash price data also shows usefulness of cash markets in providing price fluctuation information in the short run. As mentioned above, one potential explanation for this result is that many cash markets are operated by big local companies, whose prices, which incorporate information from the futures market to some extent, are largely determined by local supply and demand, and these market conditions as a whole affect futures prices. Besides, the importance of cash markets cointegrated with the futures market in providing price discovery function in both the long run and short run may partially be explained by the failure of convergence between futures and cash prices at the delivery points during the sample period in this study, which can affect the price discovery role of the futures market (Adjemian, Garcia, Irwin & Smith, 2013; Aulerich, Hoffman & Plato, 2009; Garcia, Irwin & Smith, 2011; Hoffman & Aulerich, 2013; Irwin, Garcia, Good & Kunda, 2011; Karali, McNew & Thurman, 2013).

Fourth, the vast majority of causal relationships between cash and futures prices are linear no matter whether the cash market is cointegrated with the futures market or not. However, our nonlinear Granger causality test result does support the viewpoint that the linear Granger causality test has low power in detecting nonlinear relationships among price variables which may be due to influences of market microstructure, the role of noise traders, nonlinear transaction cost functions (Abhyankar, 1996), diverse agents' beliefs (Brock & LeBaron, 1996), heterogeneous investors' goals (Peters, 1994), herd behavior (Lux, 1995), asymmetric storage behavior (Ahti, 2009), and time-varying price volatility (Nazlioglu, 2011) since the nonlinear Granger causality test provides different conclusions from those of the linear one for several cash markets. Unlike linear causal flows, nonlinear ones from futures to cash prices are common if nonlinear causality exists. Hence, with the plant level cash price data, the causality from futures to cash prices is more likely to be nonlinear, especially for cash markets cointegrated with the futures market.

Fifth, while the information share model and the common factor model draw the same conclusion about the relative contributions of the futures market and a specific cash market to the price discovery process qualitatively, i.e. the contribution of the futures market is more likely to be small than a cash market, the absolute value of the difference of the relative contributions of these two markets is larger under the common factor weight than that under the information share average.

In general, our study provides evidence that empirical results of price discovery research based on corn cash and futures markets vary with selection of cash markets. This study concentrates on futures prices directly, and future work can be extended to incorporate the interest cost and/or rate (Garbade & Silber, 1983; Yang, Bessler & Leatham, 2001; Zapata & Fortenbery, 1996). An application of symmetric and asymmetric GARCH models is also of interest to examine whether the conditional variances and covariances account for the existence of the nonlinear Granger causality.

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Appendix A: Unit Root Test

Augmented Dickey-Fuller (ADF) Test

The ADF test applies a parametric autoregression to the approximation of the ARMA structure of errors in the test regression. We need to consider $\Delta y_t = \beta' D_t + \theta y_{t-1} + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \cdots + \alpha_p \Delta y_{t-p} + u_t$, where D_t is a vector of deterministic terms such as constant and trend, and u_t is serially uncorrelated by setting p large enough. The disturbance u_t is assumed to be homoskedastic. The hypotheses are: $Null$: $\theta = 0$ vs. $Alternative$: $\theta < 0$. The number of augmenting lags can be determined by minimizing the Schwartz Bayesian information criterion (SBIC), the Akaike information criterion (AIC), or Hannan-Quinn information criterion (HQC), or lags are dropped until the last lag is statistically significant. The t-statistic, $ADF_t = t_{\theta=0} = \frac{\hat{\theta}}{se(\hat{\theta})}$, and normalized bias statistic, $ADF_n = \frac{T\hat{\theta}}{1-\hat{\alpha}_1-\cdots\hat{\alpha}_p}$, are based on the least squares estimates.

Phillips-Perron (PP) test

The PP test corrects for any serial correlation and heteroskedasticity in the error u_t of the test regression. We need to consider $\Delta y_t = \beta' D_t + \theta y_{t-1} + u_t$, where D_t is a vector of deterministic terms such as constant and trend, and u_t is $I(0)$ and may be heteroskedastic. The hypotheses are: $Null$: $\theta = 0$ vs. $Alternative$: $\theta < 0$. The test statistics are given by $PP\text{-}Z_t = (\frac{\hat{\sigma}^2}{\hat{\lambda}^2})^{\frac{1}{2}} t_{\theta=0} - \frac{1}{2}(\frac{\hat{\lambda}^2-\hat{\sigma}^2}{\hat{\lambda}^2})(\frac{T\cdot se(\hat{\theta})}{\hat{\sigma}^2})$ and $PP\text{-}Z_\theta = T\hat{\theta} - \frac{1}{2}\frac{T^2\cdot se(\hat{\theta})}{\hat{\sigma}^2}(\hat{\lambda}^2 - \hat{\sigma}^2)$, where $\hat{\sigma}^2$ is the sample variance of the least squares residual $\hat{u}_t$, and $\hat{\lambda}^2$ is the Newey-West long-run variance estimate of u_t using $\hat{u}_t$. They are consistent estimates of the variance parameters $\sigma^2 = \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} E[u_t^2]$ and $\lambda^2 = \lim_{T\to\infty} \sum_{t=1}^{T} E[\frac{1}{T}(\sum_{t=1}^{T} u_t)^2]$, respectively. Under the null hypothesis that $\theta = 0$, the Phillips-Perron $PP\text{-}Z_t$ and $PP\text{-}Z_\theta$ statistics have the same asymptotic distributions as the Augmented Dickey-Fuller t-statistic and normalized bias statistics. Two advantages of the PP test over the ADF test are: (a) we do not have to specify a lag length for the test regression; (b) the PP test is robust to general forms of heteroskedasticity in the error term u_t.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

We need to consider $y_t = \beta' D_t + \eta_t + u_t$, $\eta_t = \eta_{t-1} + \varepsilon_t$, $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$, where D_t is a vector of deterministic terms such as constant and trend, and u_t is $I(0)$ and may be heteroskedastic. The hypotheses are: $Null$: $\sigma_\varepsilon^2 = 0$ vs. $Alternative$: $\sigma_\varepsilon^2 > 0$. The test statistic is the Lagrange multiplier statistic given by $KPSS = \frac{\frac{1}{T^2}\sum_{t=1}^{T}(\sum_{j=1}^{t}\hat{u}_j)^2}{\hat{\lambda}^2}$, where $\hat{u}_t$ is the residual of a regression of y_t on D_t, and $\hat{\lambda}^2$ is a consistent estimate of the long-run variance of u_t using $\hat{u}_t$. Under the null, $KPSS$ converges to a function of standard Brownian motion which depends on the form of the deterministic terms D_t. If $D_t = 1$, $KPSS \xrightarrow{d} \int_0^1 [W(r) - rW(1)]dr$, where $W(r)$ is a standard Brownian motion for $r \in [0,1]$. If $D_t = \begin{pmatrix} 1 & t \end{pmatrix}'$, $KPSS \xrightarrow{d} \int_0^1 [W(r) +$

$r(2-3r)W(1)+6r(r^2-1)\int_0^1 W(s)ds]dr$. Critical values from the asymptotic distributions are obtained by simulation methods.

Appendix B: Cointegration Analysis and the Recursive Cointegration Approach

Cointegration Analysis

Johansen's Trace Statistic

Johansen's trace statistic, $LR_{trace}(r_0) = -T \sum_{i=r_0+1}^{p} \ln(1 - \hat{\lambda}_i)$ is likelihood ratio statistic testing the nested hypotheses:

$$null : r = r_0 \text{ vs. } alternative : r > r_0.$$

The idea is that: if $rank(\Pi) = r_0$, $LR_{trace}(r_0)$ will be small since $\hat{\lambda}_{r_0+1}, ..., \hat{\lambda}_p$ will be close to zero; if $rank(\Pi) > r_0$, $LR_{trace}(r_0)$ will be large since some of $\hat{\lambda}_{r_0+1}, ..., \hat{\lambda}_p$ will be nonzero. The asymptotic null distribution of $LR_{trace}(r_0)$ is a multivariate version of the Dickey-Fuller unit root distribution that depends on the dimension $p - r_0$ and the specification of the deterministic term. We can refer to Hansen and Juselius (1995), and Osterwald-Lenum (1992) for critical values.

Johansen's Sequential Testing Procedure

Johansen's sequential testing procedure (Johansen, 1992) is a consistent way to determine the number of cointegrating vectors. Hypotheses are tested in the following order: $H_1^*(0)$, $H_1(0)$, $H_1^*(1)$, $H_1(1)$, ..., $H_1^*(p)$, $H_1(p)$. For example, $H_1^*(1)$ can only be rejected if also $H_1^*(0)$ and $H_1(0)$ are rejected, and $H_1(1)$ can only be rejected if also $H_1^*(0)$, $H_1(0)$ and $H_1^*(1)$ are rejected. Testing is terminated and the corresponding hypothesis is accepted at the first failure to reject the null hypothesis in the testing sequence.

Johansen's Maximum Eigenvalue Statistic

Johansen's maximum eigenvalue statistic, $LR_{\max}(r_0) = -T \ln(1 - \hat{\lambda}_{r_0+1})$ is likelihood ratio statistic testing the hypotheses:

$$null : r = r_0 \text{ vs. } alternative : r = r_0 + 1.$$

The idea is similar to that of the trace statistic. The asymptotic null distribution of $LR_{\max}(r_0)$ is a complicated function of Brownian motion that depends on the dimension $p - r_0$ and the specification of the deterministic term. We can again refer to Hansen and Juselius (1995), and Osterwald-Lenum (1992) for critical values.

Hansen and Johansen's Recursive Cointegration

For a statistical model with parameter space $\theta = (\theta_1, \theta_2)$ in which we want to check constancy of θ_1, recursive analysis can be performed. Hansen and Johansen (1999) focus on two models: (a) "Z-representation" – base the recursive estimates of all parameters on the likelihood function $L^{(t)}(\theta_1, \theta_2) = \Pi_{s=1}^{t} f(X_s|X_{s-1}, ..., X_{-k+1}, \theta_1, \theta_2)$, where $X_{-k+1}, ..., X_{s-1}$ are the basis of observations for $s = 1, ..., t$; (b) "R-representation" – estimate out $\theta_2 = \hat{\theta}_2^{(T)}(\theta_1)$ using the full sample likelihood by solving $\frac{\partial \ln L^{(T)}(\theta_1,\theta_2)}{\partial \theta_2} = 0$, and then base the recursive estimates of θ_1 on the likelihood function $L_{conc}^{(t)}(\theta_1) = L^{(t)}\{\theta_1, \hat{\theta}_2^{(T)}(\theta_1)\}$. In the cointegrated VAR model, θ_1 represents the cointegrating relations, the adjustment parameters, and the error covariance, and θ_2 represents the short-run dynamics, i.e., the coefficients of the changes. The results from the "R-representation" are more relevant in recursive cointegration analysis. The derivation is shown briefly here. Let $X_t^* = (X_t^{'}, 1)^{'}$ and $\beta^* = (\beta^{'}, \delta^{'})^{'}$, Equation (1) can then be written as $\Delta X_t = \alpha \beta^{*'} X_{t-1}^* + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-1} + e_t$, for $t = 1, ..., T$. We assume the errors to be independent and Gaussian with mean zero and covariance matrix Ω, and fix the initial values X_{-k+1},..., X_0. The parameter space includes α, β^*, Γ_i for $i = 1, ..., k-1$, and Ω for some $r = 1, ..., p$. The constant term $\mu = \alpha \delta^{'}$ is restricted in a way such that the model does not allow for deterministic trend. Hence, the model is $H_1^*(r)$. Let $Z_{0t} = \Delta X_t$, $Z_{1t} = X_{t-1}^*$, $Z_{2t} = (\Delta X_{t-1}^{'}, ..., \Delta X_{t-k+1}^{'})$ and $\Gamma = (\Gamma_1, ..., \Gamma_{k-1})$. Equation (1) can be written as:

$$Z_{0t} = \alpha \beta^{*'} Z_{1t} + \Gamma Z_{2t} + e_t \text{ for } t = 1, ..., T,$$

and its maximum likelihood estimation based on all data consists of a reduced rank regression of Z_{0t} on Z_{1t} corrected on Z_{2t}. Let $R_{0t}^{(T)}$ and $R_{1t}^{(T)}$ be the residuals from regression of Z_{0t} and Z_{1t} on Z_{2t} respectively. The superscript T means that the estimation of short-run dynamics is based on the full sample. We have $R_{0t}^{(T)} = Z_{0t} - M_{02}^{(T)}\{M_{22}^{(T)}\}^{-1} Z_{2t}$, $R_{1t}^{(T)} = Z_{1t} - M_{12}^{(T)}\{M_{22}^{(T)}\}^{-1} Z_{2t}$, and $R_{et}^{(T)} = e_t - M_{e2}^{(T)}\{M_{22}^{(T)}\}^{-1} Z_{2t}$, where $M_{ij}^{(t)} = \sum_{s=1}^{t} Z_{it} Z_{jt}^{'}$, and $M_{ej}^{(t)} = \sum_{s=1}^{t} e_t Z_{jt}^{'}$ for $i, j = 0, 1, 2$. The remaining analysis is based on regression equation:

$$R_{0t}^{(T)} = \alpha \beta^{*'} R_{1t}^{(T)} + R_{et}^{(T)} \text{ for } t = 1, ..., T,$$

where $\Gamma = (\Gamma_1, ..., \Gamma_{k-1})$ has been filtered out. This equation is called the "R-representation" whose construction implies that any rejection of stability is caused by changes in the long-run structure instead of shifts in short-run dynamics. Let the product moment matrices for $i, j = 0, 1, e$ be $S_{ij}^{T(t)} = \frac{1}{t} \sum_{s=1}^{t} R_{it}^{(T)} R_{jt}^{(T)'} = \frac{1}{t}[M_{ij}^{(t)} - M_{i2}^{(T)}\{M_{22}^{(T)}\}^{-1} M_{2j}^{(t)} - M_{i2}^{(t)}\{M_{22}^{(T)}\}^{-1} M_{2j}^{(T)} + M_{i2}^{(T)}\{M_{22}^{(T)}\}^{-1} M_{22}^{(t)}\{M_{22}^{(T)}\}^{-1} M_{2j}^{(T)}]$. The maximum likelihood estimator of the cointegrating space is determined by the solution to the eigenvalue problem $|\lambda S_{11} - S_{10} S_{00}^{-1} S_{01}| = 0$, which yields eigenvalues $1 > \hat{\lambda}_1 > \hat{\lambda}_2 > \cdots > \hat{\lambda}_p > 0$ and $\hat{\lambda}_{p+1} = 0$, and eigenvectors $\hat{V} = (\hat{v}_1, ..., \hat{v}_{p+1})$ which are normalized as $\hat{V}^{'} S_{11} \hat{V} = I$. The maximum likelihood estimators of β^* and α are

$\hat{\beta}^* = (\hat{v}_1, ..., \hat{v}_r)$ and $\hat{\alpha} = S_{01}\hat{\beta}^*$. Only the space spanned by the vectors β^* can be estimated without further identifying restrictions on β^*, and $\hat{\delta}$ is contained in the last row of $\hat{\beta}^*$ such that the estimation of constant term μ can be performed as $\hat{\mu} = \hat{\alpha}\hat{\delta}'$. We use the $p - r$ smallest non-zero eigenvalues $\hat{\lambda}_- = (\hat{\lambda}_{r+1}, ..., \hat{\lambda}_p)$ to construct trace test statistic $Trace = -T\sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i)$ for cointegration rank, whereas the r largest eigenvalues $\hat{\lambda}_+ = (\hat{\lambda}_1, ..., \hat{\lambda}_r)$ are used for testing hypotheses on the cointegrating space.